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Artificial versus natural light source identification with light intensity sensors for energy monitoring

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Abstract

Studies have shown that increasing the granularity of energy consumption information in buildings could facilitate achieving energy saving objectives. Lighting systems in buildings are one of the main consumers of electricity with a share of approximately (direct and indirect) 23 percent of the total electricity in the US. Direct monitoring of lighting systems is not feasible due to challenges for instrumentation. In this study, we are proposing an approach for monitoring of lighting systems energy consumption by using single light intensity sensors. Load monitoring through light sensors is challenging due to the contribution of natural light in variation of the signal magnitude in the captured time series. Accordingly, we have proposed a new feature in frequency domain that helps us identify artificial light (AL) source type and improve AL event detection. Field experimental study showed the effectiveness of the proposed feature by eliminating all false positives in event detection.

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Keywords: Building Energy Management, Load monitoring, Lighting systems, Spectral analysis ;

1. Introduction

Building energy management is one of the major efforts in urban infrastructure management for achieving energy sustainability. Dynamics of occupants' behavior is the main driver for energy demand in buildings. This behavior could be defined in different forms including occupancy schedule, occupants' preferences, and occupants' activities/habits during their interactions with buildings. These factors are important in driving the operational schedule

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of building management systems that are in charge of two main sources of energy consumption in buildings, namely air conditioning and lighting (18% of total generated electricity in the US [1]) systems. In the United States, buildings account for ~70-75% [1, 2] of total electricity consumption.

Nomenclature

$L(n)$	likelihood ratio between light intensity signal before and after a sample point
μ, σ	mean and standard deviation values of the samples in a window before or after any point
w_{pre}	size of sampling window before any point
w_{post}	size of sampling window after any point
w^e	size of the window for voting scheme
τ_Δ	minimum acceptable signal variation for an acceptable event

Energy conservation efforts have been focused on two aspects of a) improving efficiency of physical/mechanical components by adopting high efficiency air conditioning systems, improved building envelope systems, and advanced lighting systems, and b) integrating energy-affecting human behavior factors into operation of energy management systems. The latter approaches commonly rely on understanding energy-affecting behavioral patterns [3, 4] and consequently taking actions to improve energy consumption efficiency in buildings. A category of techniques that have been at the center of attention in recent years focuses on modifying human (energy-affecting) behavioral patterns to conserve energy [5-7]. Several intervention techniques [6] have been studied to understand their effect on energy consumption patterns. The main idea in all these methods is to increase occupants' knowledge about the energy consumption patterns and how their behavior could affect that. It has been shown that by increasing the granularity of the information and adopting the effective presentation format improved energy conservation behaviors could be developed.

Energy end-use disaggregation is a technique that is used to increase granularity of information about energy consumption. The outcome could be used either for building level energy management by increasing occupants' energy awareness, at the grid level for demand-response management, or at micro-grid (neighborhood) level management. Instrumentation (sensing) at consumption node (i.e., appliance/load level) is the common practical approach for disaggregating energy consumption. Considering the cost associated with extensive instrumentation, non-intrusive load monitoring (NILM) techniques [8, 9] have been the subject of research for past few decades. NILM is centered around the notion of reducing sensing cost by limiting the number of sensing points (commonly one sensing point at building unit level) and leveraging specialized signal processing and machine learning algorithms to infer the operation of individual loads. In this paper, we are proposing a non-intrusive sensing (for load monitoring) technique that is focused on lighting systems' loads. Lighting loads are challenging in the sense that they are hard wired and direct instrumentation for electricity disaggregation is not feasible since access to wires is required.

In recent years, a number of approaches were developed for monitoring the operational modes of appliances using appliance non-electricity signals [10-12]. Light intensity sensors could be a practical alternative for inferring the operation of lighting systems since the changes in their operational states result in variation of the light intensity in the environment. These sensors could be also effective in realization and improvement of non-intrusive load monitoring techniques by introducing additional non-electricity features that facilitate the inference of the loads contributions. However, one of the major challenges in their application is the interference of natural light. Majority of the building spaces interface with the outdoor environment through windows. The variation of natural light due to presence of clouds and changes of the sun directions results in variations in the light intensity waveform, which in turn poses practical challenges on identification of artificial lights' operational states. In our previous studies [13, 14], we have developed heuristic techniques to use a single light intensity sensor in a space to identify the operational states of the artificial lights using event detection algorithms on the light intensity time series.

Considering the effects of natural light on the time series, in [13], we explored effective locations in a room for positioning the light intensity sensors and developed a semi-supervised event detection algorithm to identify the events, associated with artificial lights state changes. A state change represents on and off events. Events are defined as sharp changes on the light intensity time series. Evaluation of the proposed approach in several rooms with different geometrical characteristics and lighting fixtures' specifications showed an F-measure of 0.9 in detecting artificial lights' operations. Although this is a promising result, the requirement for sensor positioning could be a limitation in practical application of the approach.

In this study, we present the results of our exploration in developing an approach that eliminates the need for specific positioning of the light sensor in the room while improving performance of event detection algorithms. We argue that we could leverage the operational mechanisms of the light bulbs to identify their operational states and distinguish them from events associated to natural light. This could be achieved by investigating representative features in the frequency domain. Therefore, we present the concepts that were leveraged to enable the proposed approach and show the results of a field experimental study on practical application of the method.

2. Spectral Domain Artificial Light Identification

Considering the limitations that natural light effects pose on identifying operational states of artificial lights, we sought the features that could help us avoid those effects. Considering the characteristics of the AC power system, in which the flow of electric charge periodically reverses direction with a constant frequency (60 Hz) in the United States, depending on the working mechanisms, appliances that are fed through this system could reflect that frequency in their load behavior. This holds true in case of fluorescent light bulbs. These light bulbs use a device, known as ballast, to regulate the current flow through the tube. They flicker at twice fundamental frequency of the utility power. This phenomenon occurs because the power that is delivered to light bulb drops to zero twice per cycle. This mechanism is the core concept that we leveraged in proposing our approach in this study.

2.1. Filed experiments and observations

In order to explore the feasibility of leveraging spectral content of the light intensity signal and evaluate its application in developing a spectral domain event detection process, we collected data from a room for over 24 hours. A National Instrument USB DAQ with a capacity of 10KHz sampling frequency and a photodiode light intensity sensor (analog AMBI® light intensity sensor) were used for data collection. A sampling frequency of 1KHz was used for data collection. The data collection started early afternoon and ended the next day evening. During the data collection process, artificial lights in the room were triggered to on and off states for a number of times and at different times of the day to account for variations of ambient conditions. Sensor was placed close to the window in the room to assess the sensitivity of the sensor position in the results. The sensor was placed on a table, almost 60 centimeters high form the ground and was faced upwards pointing to artificial lights. The room was equipped with four conventional fluorescent light bulbs. The time stamps of the artificial light events were manually recorded in order to be used for evaluating the event detection performance.

The collected data was processed using short term Fourier transform (STFT) and the results of the analysis have been presented in Fig. 1. for the first six harmonic components except for component 300Hz. The presented plots show time series of the magnitude for each one of the harmonic contents. Since a window size of 50 samples were used for STFT analysis, the x axis unit is 0.05 seconds (compared 0.001 seconds resolution in the time domain). As this figure shows the frequency content of the even harmonic contents (i.e., 120, 240, and 360) reflect the flickering effect of the light intensity. The magnitudes are at the highest at 120 Hz and they fade away as we go higher in harmonic contents. The magnitude also is affected by the intensity of the natural light. As illustrated in 120Hz component time series, towards the end of the graph as the natural light fades away, the magnitude of frequency component increases. Therefore, the even harmonic components carry useful information that could be used for identification of the source of the light and detection of the events without errors associated to the natural light variations.

2.2. Spectral Event Detection

Events are associated with the operational states of lights in the physical environment. They are commonly reflected on the signal time series as sharp sudden changes. Therefore, an event detection algorithm seeks for sudden and sharp changes to mark them as events in the physical environment.

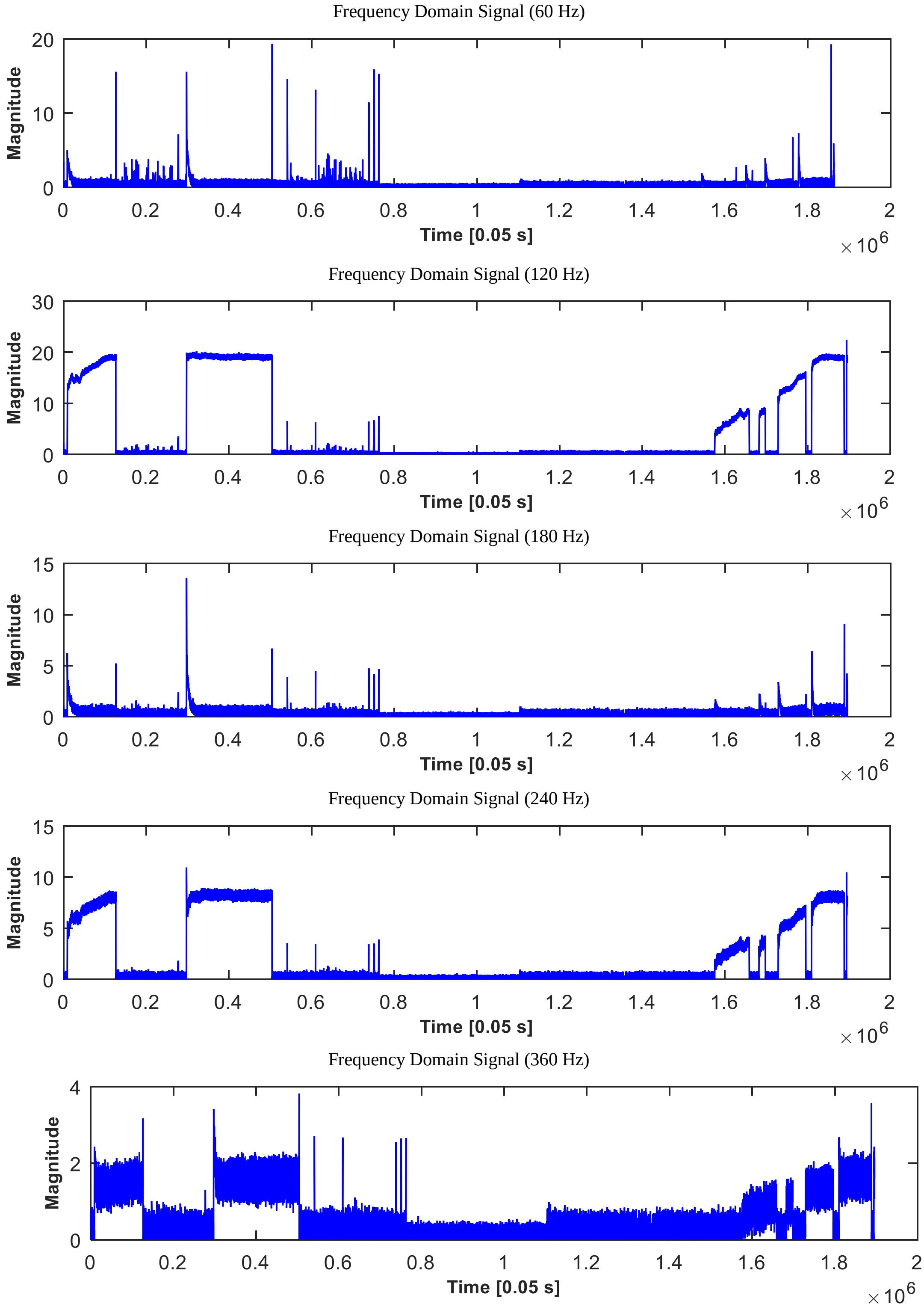

Fig. 1. Frequency content of the light signal for different harmonics

The simplest form of an event detection algorithm is the one, in which, the difference between consecutive data points on the signal time series are compared against a detection statistic, which is a threshold. Any point on the time series that has a jump larger than the threshold is identified as an event. However, due to presence of noise, this approach could result in a large number of false positives. To address the sensitivity of the algorithm, probabilistic event detection algorithms could be used. Generalized Likelihood Ratio test (GLRT) is a commonly used approach for event detection. The GLRT examines two hypotheses of H_0 and H_1 which represent the association of signal segments to a probability density function. The H_0 and H_1 hypotheses are composite hypotheses, which have unknown parameters as the signal changes over time. Therefore, unknown parameters of the $f_{H_0}(s)$ and $f_{H_1}(s)$ are replaced with the parameters obtained from the maximum likelihood estimation under H_0 and H_1: $f_{H_0}(s|\hat{\theta}_0)$ and $f_{H_1}(s|\hat{\theta}_1)$. The GLRT uses:

$$L(n) = \frac{f_{H_0}(s|\hat{\theta}_0)}{f_{H_1}(s|\hat{\theta}_1)} \underset{H_1}{\overset{H_0}{\gtrless}} \alpha$$

Where, $\hat{\theta}_i = \max_{\theta_i} f_{H_i}(s|\theta_i)$ is the maximum likelihood estimate of θ_i. The test examines the test statistic, which is the ratio between the likelihood for H_0 and H_1 using τ_{glrt} as the threshold. A Gaussian distribution is used in the GLRT test. The Gaussian distribution parameters are dynamically calculated from the signal. Thus, the algorithm uses two contiguous moving windows, w_{pre} and w_{post}, which are slid along the signal samples and then calculates the signal segments mean and standard deviation to be used for the log likelihood ratio calculation as follows:

$$L(n) = \ln \frac{P(s_i|\mu_1, \sigma_1^2)}{P(s_i|\mu_0, \sigma_0^2)}$$

$$P(s|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{\frac{-(s_i-\mu)^2}{2\sigma^2}}$$

Where s_i is the signal sample, and μ_0, σ_0^2, μ_1 and σ_1^2 are mean and standard deviation in the $[i - w_{pre} - 1, i - 1]$ and $[i + 1, i + w_{post} + 1]$, respectively. The mean and standard deviation of the signal are calculated in the windows before and after of each sample point. Once these values are calculated for each data point of signal time series, the natural log of the ratio of $P(s|\mu, \sigma^2)$ before and after each point is calculated. The points with a ratio higher than τ_{glrt} threshold could be marked as events. However, to limit false positives, as proposed in [15], a voting scheme is used to improve the performance of the algorithm. Upon calculating the $L(n)$ for all of the sample points of the signal time series, a moving detection window (that slides along the power time series one point at a time), w^e, is used along the time series and votes are assigned to each point as follows:

$$vote_{index} = \max_{w^e} L(n)$$

$$s.t. L(n) > 0$$

Votes are assigned to sample points with $L(n) > 0$. As the GLRT algorithm sweeps the time series a zero $L(n)$ value is assigned to sample points, for which $\Delta\mu = \mu_1 - \mu_0 < \tau_{\Delta P}$, in which, $\tau_{\Delta P}$ is a minimum change threshold. The minimum change threshold is defined to assure that relatively small changes do not result in event detection.

Learning from our observations from spectral analysis of the light intensity signal, we argue that by coupling the aforementioned GLRT test with the information from spectral (frequency) domain, we could segregate the artificial light from natural light and improve the performance of the event detection algorithm. Fig. 2., which illustrates the light intensity signal in both time domain and frequency domain (information from 120Hz component) for a portion of the data, shows our rationale for proposing the approach. Although in time domain several variations of light intensity (all associated with natural light) are observed, the frequency domain information does not reflect any of those changes.

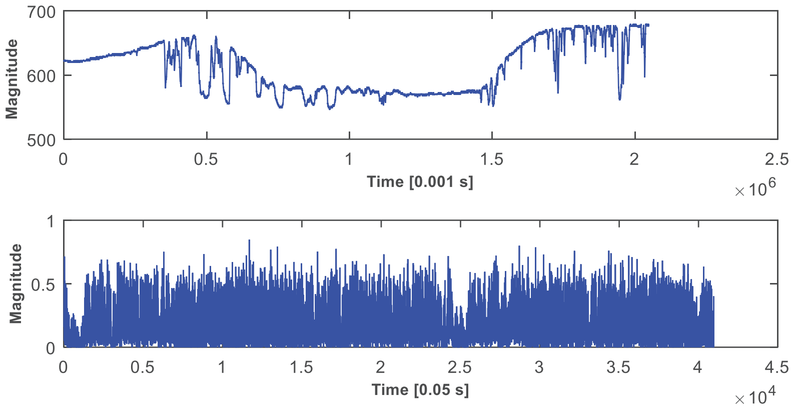

Fig. 2. Signal content comparison between time domain and frequency domain for 120Hz component (09:02:23 - 09:36:31 AM)

Fig. 3. shows the spectral event detection process. In this process the time domain signal is passed through a STFT block and the harmonic content of interest is selected. The spectral component time series is passed to event detection algorithm and the output is the list of artificial light events.

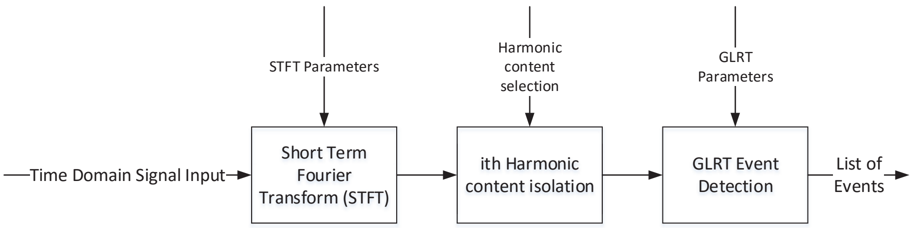

Fig. 3. Spectral event detection process for artificial light events identification

2.3. Time Domain versus Frequency Domain Event Detection

Performance of the event detection process in time domain and frequency domain were evaluated by using the aforementioned data set. Three metrics of true positives (TP), false positives (FP), and false negatives (FN) were used for performance measurement. Considering the sensitivity of the GLRT algorithm in the time domain, a tuning process for the minimum acceptable signal variation (τ_Δ) and minimum vote parameters were conducted. Table 1 shows the results of the parameter tuning. This parameter tuning was carried out on a small portion of the data.

Table 1. Parameter tuning for GLRT application in time domain

τ_Δ	10	13	15	13	13
Min Vote	10	10	10	15	20
TP	4	3	2	3	3
FP	23	19	13	16	13
FN	0	0	1	0	0

Table 2. presents the results for evaluating event detection algorithm for both time domain and frequency domain on the entire data set. TD, and FD represent time domain and frequency domain signal as input to GLRT algorithm,

respectively. Redundancy in this table points to the fact that GLRT could detect multiple events for a unique state transition (e.g., turning lights on). Therefore, we have presented the results for both conditions: with considering the redundant reported events and without them. The actual number of events in this data set is equal to 13. As Table 2 shows, the proposed feature and its associated event detection process enabled us to eliminate all the false positive detection. However, numerous false positive events were reported by using the signal in the time domain. The results shows the effectiveness of the proposed feature in identification of artificial light sources.

Table 2. Comparison between event detection algorithm performance in time domain versus frequency domain

Input signal type for event detection	TD with redundancy	TD without redundancy	FD with redundancy	FD without redundancy
TP	27	10	20	13
FP	84	33	0	0
FN	3	3	0	0

3. Conclusion

Efficient energy management in buildings calls for increasing our understanding about energy consumption distribution. Considering the major contribution of lighting loads in total energy expenditure of buildings, in this study, we proposed a novel approach for non-intrusive load monitoring of lighting systems' operations. The approach enables the application of a single off-the-shelf light intensity sensor for identification of the artificial light type and its state changes. Light intensity sensors could be easily installed in rooms and communicate their information to building occupants with suggestions for use of artificial light compared to natural light to enable green behaviors. A new feature in the frequency domain for detection of artificial versus natural light was introduced and field experimental measurements were presented to show its effectiveness in identification of both artificial light and detection of events. This feature reflects the physical characteristics of the light source. The application of this new feature in event detection processes showed considerable improvement by eliminating all false positive detections. We are planning to investigate the feasible features for other types of light bulbs such as incandescent and LED, conduct a comprehensive field validation study to evaluate the approach under diverse conditions, and explore the feasibility of quantifying energy consumption by integrating features from frequency domain and time domain as part of our future research directions.

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